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Research article

Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa

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A R T I C L E I N F O

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A B S T R A C T

Conservation agriculture, drought tolerant maize, and improved legume varieties are key climate change management strategies for smallholder farmers in southern Africa. Their complementary efforts in adaptation to climate change are sternly important for farm productivity and income. This study evaluates factors explaining individual and multiple adoption of climate change management strategies and their differential impacts on productivity and income using a sample of 1172 smallholder farmers from Malawi and Zimbabwe. The study employs multinomial logistic regression to evaluate factors of individual and multiple adoption and regression adjustment with inverse probability weighting to evaluate impacts of the different adoption regimes on farm productivity and income. The results show that multiple adoption of innovations is mostly explained by access to key resources (credit, income and information), level of education and size of land owned by the farmer. More so, the concurrent adoption of conservation agriculture, stress adapted legume varieties and drought tolerant maize has far greater dividends on productivity and income than when considered individually. However, impacts of multiple adoption of the practices are not entirely uniform across different geographic regions and gender. Results suggest that effective institutional and policy efforts targeted towards reducing resource constraints that inhibit farmers' capacity to adopt complementary climate-smart agriculture packages such as conservation agriculture, drought tolerant maize and improved legume varieties must be gender sensitive and context specific.

1. Introduction

Smallholder agriculture in Southern Africa (SA) is highly vulnerable to climate variability and change. This is mainly because the region is prone to extreme weather events such as floods, drought and heat waves (Kinuthia, 1997; Lyon, 2009; Masih et al., 2014; Nhemachena and Hassan, 2007). Drought events, extreme high temperatures and variable rainfall patterns continue to thwart agricultural production and productivity in the region and consequently general household welfare. The implications of variable climate on agriculture in SA as in the rest of the Sub Saharan Africa (SSA) region is mostly exacerbated by the over-reliance of smallholder farmers on rain-fed agriculture (Runge et al., 2004), poverty (Rockstrom, 2000), land degradation and infertile soils (Ngwira et al., 2012), poor agricultural production related policies (Clay et al., 2003), and governance related problems (Brown et al., 2007).

For countries like Zimbabwe and Malawi, agriculture remains key to livelihoods of the rural poor (Baiphethi and Jacobs, 2009; Bryceson, 2002). Agriculture remains the main source of food, employment, and income for much of the rural populace. For instance, in Malawi agriculture provides livelihoods for over 85% of the population many of which are smallholder farmers (Mangisoni, 2008; Silberg et al., 2017). Also, in Zimbabwe, over 80% of the population rely on agriculture for livelihoods, with 70% of the total population residing in rural areas. Likewise, agriculture is the main employer in the two countries with nearly over 65% of the rural populace employed in agriculture in

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Zimbabwe (Ruzivo Trust, 2013), and over 85% of the population employed in the agricultural sector in Malawi (Chinsinga and Chasukwa, 2012; Chirwa, 2004). It therefore, suggests that, effective adaptation of smallholder agriculture to climate variability and change can have profound effects on livelihoods in SA.

However, progress has been made in SSA including in the SA region in promoting adoption and use of climate-smart agriculture (CSA) innovations in agriculture particularly improved legume varieties (e.g. improved drought resistant bean (Buruchara et al., 2011), soybean, groundnut & cowpea), improved maize varieties (e.g. drought tolerant maize) (Abate et al., 2015; CIMMYT, 2013; Fisher et al., 2015), diversifying cropping systems (Makate et al., 2016; Mango et al., 2018; Waha et al., 2018), conservation agriculture practices (CA) (Giller et al., 2009; Mazvimavi and Twomlow, 2009; Nkala et al., 2011; Siziba, 2008) just to mention a few examples. Such CSA innovations are being promoted to improve productivity, farmer income, reduce poverty, tackle land degradation and minimise the negative impacts of agriculture on the environment (FAO, 2018; Lipper et al., 2014). For instance, empirical research has shown that adoption of drought tolerant maize varieties improves maize productivity, smallholder farm income and livelihoods in Zimbabwe (Lunduka et al., 2017; Makate et al., 2017b) and Malawi (Denning et al., 2009; Katengeza et al., 2016). Also, adoption of CA has been shown to yield positive impacts on farm productivity, livelihoods and reducing negative externalities of farming practices to the environment in SA including Malawi and Zimbabwe (Senyolo et al., 2018; Tambo and Mockshell, 2018; Thierfelder et al., 2016). Improved legume varieties have also been linked to improved crop productivity, farmer incomes, nutrition and many other environmental benefits (Franke et al., 2018). More so, research has shown that adoption of the individual CSA innovations is explained by resource endowment theory, psychometric and cultural theories (Deressa et al., 2009; Hassan and Nhemachena, 2008).

Different socioeconomic, institutional, and environmental attributes influence adoption of climate-smart agriculture innovations. This is particularly true for improved legumes, drought tolerant maize and CA. For example, research on drought-tolerant maize adoption show different factors (i.e. access to information, resource endowments, extension access, and gender) to explain disparity in adoption (Fisher et al., 2015; Fisher and Carr, 2015; Holden and Fisher, 2015; Holden and Quiggin, 2016; Makate et al., 2017b). Also, different socioeconomic and institutional factors shave been found to explain CA adoption in smallholder farming (Andersson and D'Souza, 2014; Chiputwa et al., 2011; Giller et al., 2009; Mazvimavi and Twomlow, 2009; Siziba, 2008). In addition, various factors have been found to explain adoption of legume varieties and their associated technologies (Makate et al., 2018; Ugochukwu and Phillips, 2018).

Despite the proven significance of drought-tolerant maize and improved legume varieties and CA in improving productivity, incomes and environmental sustainability in smallholder farming systems, little attention has been given to possible synergies and trade-offs of adopting these innovations in combination. Moreover, very little is yet known concerning the specific factors that explain the multiple adoption of improved legume varieties, drought tolerant maize and CA. It is plausible that adoption of improved legumes, drought tolerant maize varieties and CA in different combinations can have differential impacts on productivity and livelihoods and that different factors can influence different combinations of adoption. Research focusing on the impact of multiple agricultural technologies related to climate change management at farm household level in SSA is scarce but emerging. For instance, Khonje et al. (2018) found the adoption of multiple agricultural technologies (conservation farming and improved maize varieties) in Zambia to have far greater impacts on yield, income and poverty reduction than when adopted individually. Also, Tambo and Mockshell (2018) carried out his study using data from several sub Saharan African countries and found that multiple adoption of conservation agriculture (CA) pillars (crop residue, rotation and minimum tillage) had far greater impacts on income than when adopted individually. In a study by Wainaina et al. (2017) multiple adoption of input intensive and natural resources management technologies was found to have greater impacts on income than individual adoption. Also Teklewold et al. (2013b) found multiple adoption of modern seed technologies, diversification and conservation farming practices to yield greater impact on income than when adopted individually.

Against the above background, this study makes the following contributions to the literature: (i) the factors that promote or impede adoption of climate-smart agriculture innovations (improved legume varieties, drought tolerant maize and CA) individually and in combinations, (ii) examining the differential impacts of adopting climate-smart agriculture innovations (improved legume varieties, drought tolerant maize and CA) on cereal and legume productivity, farm and household income individually and in combinations, (iii) evaluating whether impacts of multiple adoption are significantly greater than adopting the individual innovations, and (iv) evaluating whether, geographical context and gender significantly influence impact trends observed in the results. This study hypothesizes that focus on adoption and impact dynamics of component CSA innovations as opposed to in combinations can underestimate or overestimate their (a) impacts and (b) the influence of various factors on technology adoption choices. It is alluded in literature that farmers can adopt and adapt multiple technologies as substitutes or complements that deal effectively with their overlapping constraints and that technology choices by farmers are path dependent (i.e. technology adopted today can be related with technology adopted in earlier seasons) (Teklewold et al., 2013a).

The rest of the paper is organized as follows: section (2) outlines the approaches followed in this study to answer research questions whilst section (3) presents study findings and discussions. Section (4) is a presentation of conclusions from the study findings and study recommendations.

2. Methods

2.1. Data and sampling

Data for this study comes from 1172 smallholder farming households gathered from Malawi and Zimbabwe. About 600 farming household from four districts (Goromonzi, Hwedza, Guruve and Mudzi) in three provinces (Mashonaland east, west and central) make up the Zimbabwean sample whilst 572 smallholder farming households from four districts (Salima, Mchinji, Dowa and Lilongwe west) found in Central province of Malawi make up the Malawian sub-sample (See Fig. 1). The data was collected in Malawi and Zimbabwe in 2011 as part of the European Commission (EC) through the International Fund for

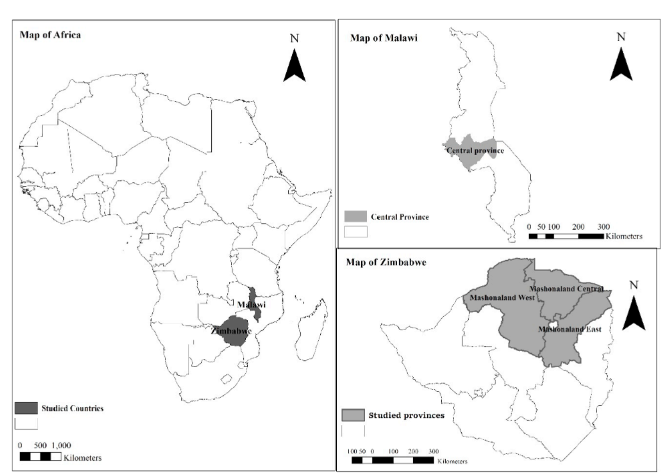

Fig. 1. Map showing the geographical location of studied countries and the respective regions/districts covered in the data collection.

Agricultural Development (IFAD) funded project named Increasing smallholder farm productivity, income and health through widespread adoption of integrated soil fertility management (ISFM) in the great lake regions and southern Africa (EC-IFAD project). The simple random sampling technique was used to select districts in selected provinces in both Zimbabwe and Malawi. The lowest sampling unit was the village. Resident agricultural extension offices in randomly sampled districts provided a list of villages found in respective districts and households. Simple random sampling techniques were then used to select villages and farming households that were interviewed. Data collection was in the form of face-to-face administration of structured questionnaires. The surveys collected vital information on several aspects of crop production, crop management, adoption of improved agricultural technologies, returns from farming, farmer livelihoods and various other aspects. Adoption of drought tolerant maize varieties, conservation agriculture and improved legume varieties (bean, soybean, groundnut, pigeon pea) was part of the information gathered.

2.2. Empirical strategy

2.2.1. Factors influencing the adoption of CSA innovations

The empirical strategy focuses on addressing two aspects. First, we analyse the factors influencing individual and multiple adoption of CSA innovations within a multinomial logistic (MNL) regression framework – a model belonging to the much broader class of what the econometrics literature classifies as discrete choice models (Greene, 2012). The MNL model is particularly appropriate in modelling choice behaviour, where perceived outcomes are modelled in terms of the characteristics of the individuals, smallholder farmers, in our case. To formalise the MNL model, let Y_i denote the random variable that indicates the choice made by smallholder farmer i, then, under certain assumptions, the probabilities of choosing or adopting CSA technologies can be expressed as follows (Greene, 2012):

$$Prob(CSA_i = j|x) = \frac{exp(x'\beta_j)}{1 + \sum_{h=1}^{J} exp(x'\beta_h)} \tag{1}$$

where β_j is a $K \times 1$ vector and each smallholder farmer is faced with choices $j = 1,2, \ldots\ldots,J$. The outcome, CSA_i comprises of eight categories formed from a combination of three climate-smart innovations namely: drought tolerant maize (DTM), improved legume (IL), and conservation agriculture (CA), which are all dummy variables to indicate adoption of such technologies. A concatenation of these three variables makes the following eight categories that make the variable CSA_i: that is, (a) no adoption (the base category), (b) CA adoption only, (c) IL adoption only, (d) IL and CA adoption, (e) DTM adoption only, (f) DTM and CA adoption, (g) DTM and IL adoption, and (h) DTM, IL, and CA adoption. The vector x (see Table 1 for a complete list of the variables included in the analysis) contains conditioning variables measuring different household-level demographic, institutional, social, economic and environmental characteristics. Choice of these explanatory covariates was mostly guided by resource endowment, psychometric, cultural theories that link adoption dynamics of climate change management strategies to various socioeconomic, behavioural and cultural factors (Deressa et al., 2009; Hassan and Nhemachena, 2008; Nhemachena and Hassan, 2007). For instance, farmers with better access to resources (knowledge, finance, and labour) are more inclined to adopt new agriculture technologies compared to their relatively resource-poor counterparts. Also, cultural practices, mental abilities and farmer behavioural styles can impact on farmer perceptions regarding technologies and hence influence their adoption.

Consistent estimation of equation (1) requires that the probability of choosing a combination of CSA innovations by any given smallholder farmer be independent from the probability of choosing a different combination – the well-known assumption of independence from irrelevant alternatives (IIA) (McFadden, 1973). The IIA assumption is formally tested in this study using the Hausman test with a null hypothesis that IIA holds against an alternative hypothesis that the IIA assumption is violated. Given that the coefficient estimates from a MNL model are difficult to interpret and only provide the direction of effect or association of the explanatory variables on the outcome variable but do not represent the actual magnitude of change, marginal effects, which show the magnitude of change in the outcome variable due to a unit change in the explanatory variable (Greene, 2012) are reported. Following Greene (2012), differentiating equation (1) gives the marginal effects of the attributes, x on the probabilities, and expressed as follows:

$$\delta_j = \frac{\partial P_j}{\partial x_i} = P_j[\beta_j - \sum_{k=0}^{J} P_k \beta_k] = P_j[\beta_j - \bar{\beta}] \tag{2}$$

where, δ_j is the marginal effect associated with choosing category j, the parameter β_j is the coefficient estimate associated with choice j which is calculated through equation (1) and $\bar{\beta}$ represents the average of the regression coefficients. All the analysis is conducted using Stata's *mlogit* command with the base category chosen as "no adoption". The MNL model has been applied in several other studies that explore the factors associated with multiple adoption of farming innovations (see e.g. (Deressa et al., 2009; Hassan and Nhemachena, 2008; Kurukulasuriya and Mendelsohn, 2007; Tambo and Mockshell, 2018; Teklewold et al., 2013a)). Moreover, the MNL model is relatively easy to apply and is perfectly suited for multi-category, individual-level analysis where there is no specific importance in the ordering of the outcome variable (Deressa et al., 2009; Greene, 2003; Tse, 1987).

2.2.2. The impact of multiple CSA innovations on productivity and income

Second, we examine the impact of adopting multiple CSA technologies on maize productivity and income. The empirical approach to examine the potential relationship abstracts from a random utility framework in which a smallholder farmer adopts a specific CSA innovation or a combination of technologies only if the expected difference between the utility of adoption versus non-adoption is positive (i.e. adoption is better) (Greene, 2012; Heckman et al., 2001). The adoption of CSA technologies is not randomly assigned, and many farmers may decide to adopt or not adopt a technology depending on unobservable characteristics. Also, adopters of certain innovations or combination of innovations may differ systematically with their non-adopting counterparts thereby resulting in potential self-selection bias. The model we estimate addresses these issues to generate more credible estimates of the impact of adoption of CSA innovations on smallholder farmer livelihoods.

The basic formulation of the model including some terminologies is adapted from Lechner (2001). To motivate this model, consider the following potential outcomes , faced by a smallholder farmer adopting (J) different and mutually exclusive climate-smart technologies or choices. Each smallholder farmer adopts only one out of the possible J choices where the choice '1' represents no adoption (the base category) and '8' represents adoption of all the three strategies as described earlier. Thus, for each smallholder farmer, only one outcome variable is observable in the data and the remaining outcomes represent the counterfactuals. Adoption of a particular climate-smart technology is represented by the variable, CSA_i as mentioned earlier. Following the potential outcomes approach developed in Rubin (1974), the observed outcome of each smallholder farmer can be summarised or expressed in terms of the multiple treatment indicator and given as follows:

$$\log Y_i = \sum_{j=1}^{J} D_{ij}(CSA_i)\log Y_i \tag{3}$$

where $\log Y_i$ represents the potential outcome variables (all expressed in logarithms): cereal and legume productivity, farm income, and total household income of the i^{th} smallholder farmer; CSA_i is the multiple treatment variable is described earlier; $D_{ij}(.)$ is the treatment dummy

Table 1
Summary statistics of analysis variables by country.

Variable	Variable descriptions and measurement	Malawi mean	Zimbabwe mean	Overall sample mean
househ_male	Binary variable = 1 if farmer is male; 0 otherwise	0.820	0.757	0.788
househ_married	Binary variable = 1 if farmer is married; 0 otherwise	0.820	0.744	0.781
househ_age	Age of household head in years	43.135	51.420	47.376
househ_size	Household size	5.867	5.384	5.620
workers	Number of workers available to work in the field	3.274	3.195	3.234
emp_farmer	Binary variable = 1 if household head is a full-time farmer; 0 otherwise	0.955	0.864	0.908
landsize	Land size holding	1.570	2.344	1.967
cultivt_legms_prev	Binary variable = 1 if farmer cultivated legumes before; 0 otherwise	0.942	0.897	0.919
Ext_acc	Binary variable = 1 if household's has had contact with extension; 0 otherwise	0.463	0.612	0.540
credit_acc	Binary variable = 1 if farmer has access to credit; 0 otherwise	0.269	0.118	0.192
Fertilizer	Binary variable = 1 if farmer has had access to inorganic fertilizer; 0 otherwise	0.913	0.865	0.888
Atleast_sec	Binary variable = 1 if farmer had attained at least secondary education; 0 otherwise	0.138	0.478	0.312
Bicycle	Binary variable = 1 if farmer owned a bicycle; 0 otherwise	0.663	0.376	0.516
Cattle	Binary variable = 1 if farmer owned cattle; 0 otherwise	0.093	0.571	0.338
Good_RdCond	Binary variable = 1 if farmer's road to the nearest market was in good condition; 0 otherwise	0.554	0.393	0.471
dist_twn	Distance to the nearest town in kilometers	61.268	97.796	79.984
Cereal_pdctv	Cereal productivity in kg per hectare	2450.923	1589.324	2009.473
Leg_pdctv	Legume productivity in kg per hectare	1178.213	1320.888	1251.314
Total_inc	Total yearly household income in USD	618.950	607.499	613.083
Farm_inc	Total yearly farm income in USD	444.248	322.147	381.688
Observations		572	601	1173

Data Source: Data for this study comes from smallholder farming households from Zimbabwe and Malawi.

variable that takes one if the smallholder farmer i adopted CSA strategy j and zero otherwise; X is a vector of household-level characteristics; and u_i is a disturbance term. Legume productivity is calculated as the amount of legumes dry harvest (in kilograms) divided by total land allocated to legumes (in hectares). The legumes considered in the calculation of legume productivity include common bean (*Phaseolous vulgaris*), groundnut, soybean, and pigeon pea. Cereal productivity is proxied by maize yield (maize output in kgs divided by the area set aside for maize production). Farm income is the total earnings the farmer received after selling farm produce in a year while total income includes both farm and non-farm income from members within the same household.

Equation (3) can further be expressed in terms of a multivariable linear regression equation where livelihood outcomes (i.e. all measured as continuous variables) are both a function of the multiple treatment variable, CSA_i and the vector, X, of pre-treatment smallholder farmer-level characteristics and expressed as follows:

$$\log Y_i = \alpha_0 + \alpha_1 CSA_i + X'\gamma + u_i \tag{4}$$

In equation (4), the logarithm of each outcome variable is regressed on the vector, X, separately for each treatment level and the predicted outcome for each smallholder farmer is calculated using the data for those farmers adopting the specific level of CSA technology.

To generate a consistent and more credible impact of adoption of CSA strategies, the study relies on inverse-probability-weighted regression adjustment (IPWRA) to control for potential selection bias associated with the multiple adoption decision. The IPWRA estimator, first computes a generalised propensity score (GPS) – defined as the conditional probability of receiving a specific treatment given a set of pre-treatment characteristics and computed as follows (Imbens, 2000):

$$gps(csa, x) \equiv pr(CSA = csa|X = x) = E\{D(csa)|X = x\}$$

The GPS, $gps(csa, x)$ is estimated using a MNL model as described earlier and is then used as a weighting function to calculate the average potential outcomes and expressed for each level of treatment as follows (Imbens, 2000):

$$E\left[\frac{\log Y_i D_{ij}(CSA_i)}{gps(csa, X)}\right] = E[\log Y_i] \tag{5}$$

The expression $\frac{D_{ij}(CSA_i)}{gps(csa, X)}$ represents the inverse probability of treatment weights (IPTW). As a second step, the outcome model in equation (4) is then fitted by a weighted regression for each CSA treatment choice and thereby generating treatment-specific predicted outcomes for each smallholder farmer. The last step encompasses computing the expected means of the treatment-specific predicted outcomes. The average treatment effect can be computed by comparing the computed potential outcome means between arbitrary CSA strategies; for instance, CSA strategy m versus strategy k, and expressed as follows:

$$\hat{\tau}_{mk}^{we} = \frac{1}{N}\sum_{i=1}^{N}\frac{\log Y_i D_{im}(CSA_i)}{\hat{gps}(m, X_i)} - \frac{1}{N}\sum_{i=1}^{N}\frac{\log Y_i D_{ik}(CSA_i)}{\hat{gps}(k, X_i)}$$
$$= \hat{\mu}_m - \hat{\mu}_k \tag{6}$$

where $\hat{\tau}_{mk}^{we} = \hat{\mu}_m - \hat{\mu}_k$ is the average treatment effect found by comparing CSA strategy m versus strategy k, $\hat{gps}(m, X_i)$ is the estimated generalised propensity score and the superscript 'we' represents the weighting method (Uysal, 2015). In this study, the average treatment effect on the treated (ATET) sample is reported making the assumption that the conditional independence and overlap assumptions hold (Imbens, 2000; Uysal, 2015). The ATET measures the effect of adopting a particular CSA strategy compared to not adopting a strategy at all. To calculate the ATET, Stata's *teffects ipwra* command which uses a one-step GMM approach to compute correct standard errors of the ATET that incorporate the calculated generalised propensity score is used (StataCorp, 2017).

3. Results and discussions

3.1. Description of climate-smart agriculture innovations, household characteristics, farm productivity and incomes

3.1.1. Adoption rates for the three climate-smart innovations

Improved legumes (IL) are essential for improving soil fertility (through biological nitrogen fixation) and their drought, disease and pest resistant traits make them well adapted to increased pest and water shortage stress that surge with climate variability and change. CA is important for improving soil fertility, conserving soil moisture and regulation of soil temperature which makes it an important climate stress management strategy for farmers. Also, drought tolerant maize (DTM) is high yielding and it is well-adapted to moisture stress. In Fig. 2, adoption rates for the three climate-smart innovations (DTM, CA and IL) individually and in combination are shown. Non-adoption in the full sample was 24.7% with 28.8% and 20.8% in Malawi and Zimbabwe

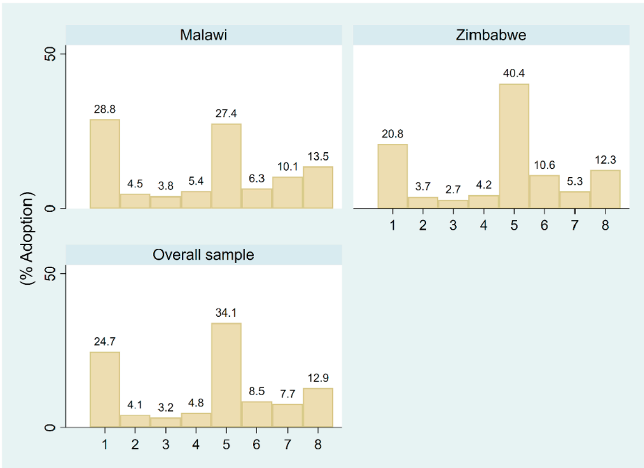

Fig. 2. The adoption rates of climate-smart agriculture practices considered in the study for Malawi, Zimbabwe, and overall sample. Notes: CSA adoption categories: 1 = no adoption; 2 = Conservation agriculture (CA); 3 = Improved legume (IL); 4 = IL and CA; 5 = Drought tolerant maize (DTM); 6 = DTM and CA; 7 = DTM and IL; 8 = DTM, IL, and CA.

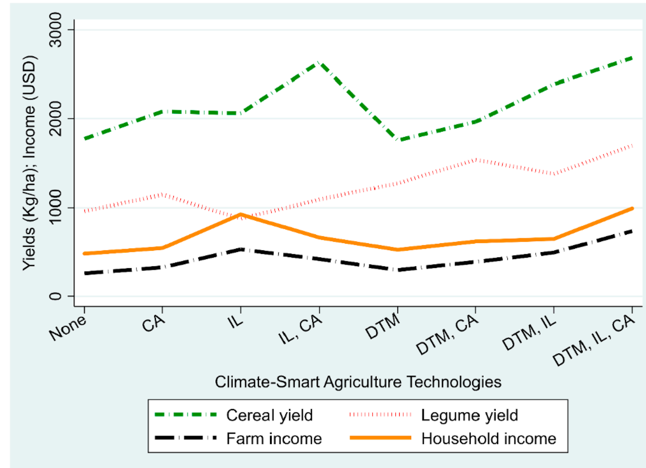

Fig. 3. Distribution of smallholder productivity and income by climate-smart agriculture innovation adoption regimes.

respectively. As for CA, adoption rates were low with 4.5, 3.7, and 4.1% adoption rates in Malawi, Zimbabwe and full study sample respectively. Low adoption rates are also observed for improved legume, only 3.2% in the full sample and 3.8% in Malawi compared to 3.2% in the Zimbabwe sub-sample. Adoption rates of DTM are overwhelmingly high in the studied sample with 34.1, 40.4 and 27.4% adoption rates in full sample, Zimbabwean sample and Malawian sample respectively.

Coming to adoption in combination, IL& CA had 5.4 and 4.2% in Malawi and Zimbabwe respectively. Overall, IL & CA adoption was 4.8%. DTM & CA had slightly higher adoption rates with full sample rate at 8.5%, and 10.6 and 6.3% adoption rate in Zimbabwe and Malawi respectively. Also, adoption of DTM&IL had rates of 10.1% in Malawi, 5.3% in Zimbabwe and 7.7% in the whole sample. As for adoption in combinations, implementation of the three innovations was highest, with 12.9% rate in full sample, with 13.5 and 12.3% adoption rates in Malawi and Zimbabwe respectively.

3.1.2. *Characterization of sampled farmers (socioeconomic characteristics)*

Characteristics of studied smallholder farmers are shown in Table 1. The sample was dominated by male farmers with 82, 76, and 79% male representation in Malawi, Zimbabwe and entire sample respectively. Most of the respondents were married with marriage rate at 82% in Malawi and 74.4% in Zimbabwe. Farmers in Malawi were relatively young with mean age at 43.1 years compared to 51.4 years in Zimbabwe. Farmers in Zimbabwe were more educated with 48% of farmers sampled with at least secondary education compared to 14% in Malawi. Also, mean household size was slightly higher in Malawi (5.9) compared to 5.4 in Zimbabwe. Related, average labour per household was 3.3 in Malawi compared to 3.2 persons in Zimbabwe. About 96% of the farmers indicated they were into fulltime farming in Malawi compared to 86 in Zimbabwe. Average land size holding owned was slightly higher in Zimbabwe (2.34 ha) as compared to 1.57 ha in Malawi.

Farmers in both countries indicated that legume cultivation was and has been their thing in the past as 94% indicated that they had cultivated legumes before survey date in Malawi compared to 90% in Zimbabwe. Access to extension services in Zimbabwe was higher (61%) as compared to 46% in Malawi. Also, credit access was slightly higher in Malawi (27%) when compared to Zimbabwe (12%). Access to fertilizer was also comparably higher in Malawi (91%) compared to Zimbabwe (87%). In terms of assets, 66% of farmers in Malawi owned bicycles as compared to only 38% in Zimbabwe. Also, cattle ownership was very low in Malawi (9%) compared to 57% in Zimbabwe. Almost 55% of sampled farmers in Malawi indicated the state of the main road to nearby main market was still good compared to 39% in Zimbabwe. Average distance to the nearest town was about 61 km in Malawi compared to 98 km in Zimbabwe (see Table 1).

3.1.3. *Cereal and legume productivity and income by CSA innovation adoption*

Average statistics for cereal productivity, legume productivity and income are also shown in Table 1. The average cereal productivity in Malawi was about 2.5 tons compared to 1.6 tons in Zimbabwe. Also, legume productivity was about 1.2 tons in Malawi compared to 1.3 tons in Zimbabwe. Average household income was US$619 in Malawi compared to US$608 in Zimbabwe. Also, average farm income in the Zimbabwean sample was US$322 compared to US$444 in Malawi.

In Fig. 3 average statistics for the four outcome variables are shown by CSA adoption regime. Generally, cereal productivity, legume productivity, farm and total household income are comparably higher for combination of CSA innovations adopted compared to no adoption and even adoption of single CSA innovations. For instance, average cereal productivity for farmers who adopted all the CSA innovations (DTM, IL &CA) is highest (2.7 tons), average legume productivity for similar adoption regime is also highest (1.7 tons). Similar trends for farm and household income are also observed in Fig. 3. Farmers who adopted all the three innovations are better off in terms of income streams. For cereal productivity, combination of IL and CA was also very effective as shown by very high mean cereal yield (2.6 tons). No adoption in most cases yielded less in productivity and income for the farmer. Overall, results show that adoption of innovations positively relates to cereal and legume productivity and incomes. More so, adoption of the full package relates to the best dividends for the farmer in terms of cereal, legume productivity and income.

3.2. *Factors affecting adoption of climate-smart agriculture innovations in isolation and in combination*

Results from MNL regression are reported here to tell the determinants of adopting individual and or a suite of CSA innovations (IL, CA & DTM) in combination. Bias in focus is put on interpreting and discussing results on factors that influence multiple adoption of innovations particularly the full set (IL, CA & DTM) as a huge gap still exists in literature on that aspect. The base category used in the analysis was non-adoption. The Hausman specification test showed that coefficients from the MNL regression results were independent of additional alternatives. Dropping a single alternative at a time was shown not to significantly change coefficients of the MNL regression, the χ^2 values ranged

Table 2
Multinomial logit regression estimates: Factors influeincing single and multiple adoption of climate-smart agriculture innovations in Malawi and Zimbabwe.

Variables	CA	IL	IL & CA	DTM	DTM & CA	DTM & IL	DTM,IL & CA
househ_male	0.159	0.477	1.110*	−0.0153	−0.172	0.316	0.504
	(0.779)	(0.793)	(0.662)	(0.350)	(0.607)	(0.576)	(0.538)
househ_married	−0.521	−0.0446	−1.072*	0.466	0.105	−0.819	−0.255
	(0.760)	(0.773)	(0.618)	(0.358)	(0.611)	(0.569)	(0.521)
Log_Total_inc	0.0533	0.228	0.0726	0.0470	0.0127	0.0668	0.191**
	(0.122)	(0.146)	(0.113)	(0.0485)	(0.0754)	(0.0928)	(0.0822)
househ_size	0.0842	−0.256**	−0.132	−0.0423	0.132**	0.00383	−0.0102
	(0.0891)	(0.120)	(0.0950)	(0.0473)	(0.0648)	(0.0728)	(0.0628)
househ_age	−0.0371**	−0.00772	−0.00904	−0.000752	−0.0164	−0.00810	−0.000837
	(0.0153)	(0.0140)	(0.0127)	(0.00632)	(0.0105)	(0.0106)	(0.00894)
workers	−0.0521	0.0864	0.127	0.0400	0.141	0.0268	0.0388
	(0.145)	(0.170)	(0.140)	(0.0715)	(0.106)	(0.111)	(0.0953)
landsize	0.474***	0.169	0.347***	0.185**	0.372***	0.386***	0.362***
	(0.0962)	(0.173)	(0.118)	(0.0886)	(0.0964)	(0.0972)	(0.0942)
emp_farmer	−0.218	−0.182	−0.226	−0.00879	0.385	0.00679	0.0203
	(0.612)	(0.613)	(0.550)	(0.291)	(0.479)	(0.505)	(0.408)
cultivt_legms_prev	0.389	0.285	−0.0636	0.482*	1.823**	1.104*	1.541***
	(0.653)	(0.656)	(0.525)	(0.267)	(0.759)	(0.631)	(0.571)
Ext_acc	2.033***	1.286***	2.109***	0.180	1.762***	1.161***	1.996***
	(0.402)	(0.388)	(0.425)	(0.177)	(0.297)	(0.276)	(0.266)
credit_acc	−0.551	−0.241	1.534***	0.317	−0.0383	0.0264	0.655**
	(0.455)	(0.485)	(0.359)	(0.255)	(0.338)	(0.333)	(0.278)
Atleast_sec	−0.0237	0.319	0.397	0.114	0.217	0.331	0.586**
	(0.434)	(0.471)	(0.415)	(0.215)	(0.320)	(0.339)	(0.285)
Bicycle	0.755*	−0.235	−0.219	0.393**	0.828***	0.366	0.0595
	(0.386)	(0.402)	(0.359)	(0.183)	(0.287)	(0.292)	(0.251)
Cattle	0.0947	0.739	0.757*	0.0256	0.256	−0.296	0.306
	(0.446)	(0.475)	(0.424)	(0.217)	(0.318)	(0.361)	(0.292)
Good_RdCond	0.593*	0.420	0.473	0.0352	0.591**	0.283	0.445*
	(0.346)	(0.375)	(0.321)	(0.172)	(0.259)	(0.263)	(0.228)
log_dist	−0.436***	0.724**	0.192	−0.159*	−0.0273	0.243	−0.130
	(0.149)	(0.289)	(0.216)	(0.0858)	(0.140)	(0.166)	(0.124)
Fertilizer	−0.664	0.249	−0.298	0.792***	0.971**	1.036**	1.265***
	(0.435)	(0.537)	(0.433)	(0.254)	(0.479)	(0.505)	(0.448)
geo_mash_east	0.863	−0.0788	−0.670	0.734***	0.373	0.255	−0.106
	(0.536)	(0.613)	(0.537)	(0.252)	(0.364)	(0.445)	(0.349)
geo_Central	0.482	0.977	0.446	−0.406	−0.676	0.601	0.0426
	(0.584)	(0.607)	(0.535)	(0.254)	(0.418)	(0.439)	(0.362)
Constant	−1.510	−7.433***	−4.698***	−0.662	−5.805***	−5.848***	−6.593***
	(1.434)	(1.879)	(1.534)	(0.668)	(1.337)	(1.339)	(1.167)
Base outcome = No adoption			**LR chi squared = 558.26*** **			**Pseudo R2 = 13.45**	
Observations	1172	1172	1172	1172	1172	1172	1172

Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1; CA = Conservation agriculture; IL = improved legume; DTM = Drought tolerant maize.

between 4 and 19 with statistically insignificant p-values at 5% level (showing independence of irrelevant alternatives). Tables 2 and 3 report coefficients and marginal effects from MNL regression respectively. Marginal effects (Table 3) are reported and discussed here. In this instance, the marginal effects measure the expected change in probability of a certain choice (of a CSA innovation or combination of innovations) being made with respect to a unit change in an explanatory variable, all in comparison to the no adoption category.

3.2.1. *Factors explaining adoption of individual CSA innovations*

In all cases, results are compared to the base category of no-adoption. Results show that adoption of CA is negatively associated with age of farmer, access to inorganic fertilizers, and distance to town and positively associated with land size holding, and access to extension services. Results imply that probability of adopting CA decreases with ageing of farmer possibly due to risk aversion of innovative practices like CA by older farmers. Also access to fertilizers can discourage farmers to adopt CA, since CA itself is part of the soil fertility correction mechanism for smallholder farmers. Also, more distance to market may increase transaction costs of accessing input and output markets and this can discourage CA adoption. The positive association of CA adoption with land size imply that larger plot sizes could be more flexible to experiment with CA. Lastly, positive association of extension could be due to information advantage for farmers with access to it. The factors of CA adoption concur with vast literature see for example, Mazvimavi and Twomlow (2009) and Knowler and Bradshaw (2007).

Also, adoption of IL is negatively associated with household size and positively associated with distance to town and central region. Results could be pointing to the fact that adoption of improved legume varieties is less likely in households overburdened by bigger family members to support. More so, results, point to the fact that the central region of Malawi positively enhance chances of adopting IL possibly due to inherent factors unique to the region. Distance to town was found to be positively related to adoption of improved IL varieties this could possibly be due to massive advertising (seed suppliers active at local community level) and availability of community seedbanks that could possibly offset the usual negative influence of distance to town.

Adoption of DTM was positively and significantly associated with married farmers, extension access, credit access, income and being located in Mashonaland east province of Zimbabwe and negatively associated with distance to town and being located in central province of Malawi. Results imply that marriage as an institution is important for adopting DTM and that income and credit enhances probability of adopting DTM. Income or capital access enhances flexibility of the farmer in accessing complementary inputs for DTM. Extension is critically important for availing necessary information on DTM. Also distance to town could decrease probability of adopting DTM due to increasing transaction costs with more distance. Also geographical

Table 3
Marginal probability effects of the factor influencing single and multiple adoption of climate-smart agriculture practices in Zimbabwe and Malawi.

	CA	IL	IL & CA	DTM	DTM & CA	DTM & IL	DTM,IL & CA
househ_male	−0.000	0.009	0.039	−0.039	−0.029	0.011	0.036
	(0.027)	(0.023)	(0.025)	(0.060)	(0.040)	(0.035)	(0.047)
househ_married	−0.018	0.001	−0.042*	0.132**	0.013	−0.057*	−0.019
	(0.026)	(0.022)	(0.023)	(0.060)	(0.039)	(0.035)	(0.044)
Log_Total_inc	0.001	0.006	0.001	0.021***	−0.002	0.002	0.018**
	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)	(0.006)	(0.007)
househ_size	0.004	−0.008**	−0.005	−0.009	0.012***	0.001	0.000
	(0.003)	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)	(0.005)
househ_age	−0.001**	−0.000	−0.000	0.001	−0.001	−0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
workers	−0.002	0.002	0.005	0.008	0.013*	0.001	0.003
	(0.005)	(0.005)	(0.005)	(0.011)	(0.007)	(0.007)	(0.008)
landsize	0.009****	−0.002	0.004	−0.003	0.010***	0.012***	0.013***
	(0.002)	(0.005)	(0.004)	(0.011)	(0.004)	(0.004)	(0.005)
emp_farmer	−0.009	−0.006	−0.010	−0.006	0.030	−0.000	0.001
	(0.021)	(0.018)	(0.021)	(0.047)	(0.031)	(0.032)	(0.035)
cultivt_legms_prev	−0.014	−0.011	−0.036*	−0.032	0.087	0.031	0.096*
	(0.023)	(0.019)	(0.020)	(0.051)	(0.054)	(0.042)	(0.055)
Ext_acc	0.041***	0.013	0.047***	0.155****	0.063****	0.018	0.117****
	(0.014)	(0.010)	(0.016)	(0.026)	(0.019)	(0.015)	(0.023)
credit_acc	−0.024	−0.010	0.062****	0.091**	−0.008	−0.003	0.067***
	(0.015)	(0.013)	(0.013)	(0.039)	(0.020)	(0.019)	(0.021)
Atleast_sec	−0.009	0.004	0.007	−0.016	−0.001	0.009	0.043*
	(0.015)	(0.014)	(0.016)	(0.033)	(0.020)	(0.020)	(0.024)
Bicycle	0.018	−0.015	−0.020	0.043	0.044**	0.008	−0.025
	(0.013)	(0.012)	(0.014)	(0.029)	(0.018)	(0.018)	(0.021)
Cattle	−0.001	0.019	0.026	−0.020	0.010	−0.032	0.018
	(0.015)	(0.014)	(0.016)	(0.034)	(0.019)	(0.022)	(0.024)
Good_RdCond	0.013	0.006	0.009	−0.044	0.027*	0.003	0.021
	(0.012)	(0.011)	(0.012)	(0.027)	(0.016)	(0.016)	(0.019)
log_dist	−0.016***	0.024***	0.009	−0.035***	0.002	0.021**	−0.013
	(0.005)	(0.009)	(0.008)	(0.013)	(0.009)	(0.010)	(0.010)
Fertilizer	−0.049***	−0.010	−0.040**	0.076	0.028	0.034	0.081*
	(0.015)	(0.016)	(0.017)	(0.046)	(0.033)	(0.033)	(0.042)
geo_mash_east	0.023	−0.010	−0.038*	0.131****	0.007	−0.000	−0.042
	(0.018)	(0.018)	(0.021)	(0.038)	(0.021)	(0.027)	(0.028)
geo_Central	0.021	0.032*	0.019	−0.096**	−0.051*	0.048*	0.009
	(0.020)	(0.018)	(0.021)	(0.042)	(0.027)	(0.028)	(0.031)
Observations	1172	1172	1172	1172	1172	1172	1172

Standard errors in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, $^{****}p < 0.001$; CA = Conservation agriculture; IL = improved legume; DTM = Drought tolerant maize.

variables significantly influence probability of adopting DTM because of different geographic specific contexts. For example Mashonaland east province is one of the main maize growing regions in Zimbabwe which could explain positive influence of the district on DTM adoption (Makate et al., 2017b).

3.2.2. Factors explaining adoption of a combination of CSA innovations

Results show discernible differences in factors explaining adopting different pairs of CSA innovations. Adopting IL & CA was positively associated with access to extension and credit and negatively associated with married farmer, having cultivated legumes before, access to fertilizer and residing in Mashonaland east province of Zimbabwe. Access to resources and information chiefly explains the positive association of adopting the pair with access to credit and extension. Access to fertilizer could discourage adoption of the pair (CA & IL) as the pair is good for enhancing soil fertility hence to some extent adoption of the combination could act as a substitute for fertilizer. The negative influence of the marriage institution could be implying that not being married is not a serious constraint for adopting the pair.

Adoption of DTM & CA was found to be positively associated with household size, number of workers, land size, ownership of a bicycle, extension access, and good road condition. The result implies access to labour chiefly increase chances of adopting the pair. Also, larger pieces of land increases chances of adopting the pair possibly due to the increasing returns on CSA innovations with larger farms (Bidogeza et al., 2009). Ownership of bicycle enhances mobility of the farmer which can enhance access to information and inputs from distant markets and hence increases odds of adopting the pair. Good road condition also reduces transaction cost of accessing markets and hence positively associates with adopting the pair. Access to extension chiefly enhances access to information which positively correlates with adoption of the pair (DTM&CA).

Adopting DTM and IL was also positively correlated with land size holding, distance to town, and region (Central region). As alluded to earlier, land size can increase economies of scale from innovations which explains the positive association of adopting the pair with land size. Also, increasing participation of local institutions in seed supply for both legumes and maize varieties could explain the positive association of adopting the pair with distance. With easy access of innovations at local level distance will not significantly influence transaction costs that may discourage adoption. Adopting the pair was however, negatively associated with farmer being married. This could imply that among the single headed families (e.g. widowed), the need (propensity) to adopt the pair of innovations to positively influence household welfare could be more as compared to married and stable families.

Coming to adoption of the complete package of DTM, CA, & IL, income, land size, cultivating legumes before, extension, credit, education and access to fertilizer positively explained adoption. The results communicate that when it comes to adopting the full set of innovation, access to resources chiefly matter. Access to information through extension, and access to financial resources through credit, access to

fertilizer and household income become critically important for adoption. Fertilizer is a necessary complementary input for adopting the CSA innovations hence access to it enhances the propensity to adopt them. This concur with literature which show the importance of wealth or financial resources in adopting related agricultural innovations (Bidogeza et al., 2009; Deressa et al., 2009; Hassan and Nhemachena, 2008; Makate et al., 2018; Mazvimavi and Twomlow, 2009). Also results show that land size positively associates with propensity to adopt the full-set of innovations. This could be because, with larger land size, farmers can be flexible to experiment with the innovations which eventually increases their chances of fully adopting them. Also, larger land size can enhance economies of scale of adopting the full set. Likewise, and unlike adopting other combinations, education positively explains adopting the full set of CSA innovations. This could be because, knowledge demands increase with number of innovations adopted hence farmer with more education are likely to understand implementation of the innovations and hence get the best out of them. Also, having cultivated legumes before was also critically important in explaining adoption of the full set. Farmers who have cultivated legumes before possibly understand more the benefits of intercropping legumes with cereals (i.e.) and further having CA in that mix and this possibly explains the result.

3.3. Impact of a package of climate-smart agriculture innovations on productivity and income

Table 4 displays the results of the doubly robust IPWRA estimator that was adopted to evaluate impact of CSA innovations on productivity and income. Adoption impacts of individual innovations and a combination of innovations are compared to no adoption in all cases i.e. the no adoption group is the control. Results generally show that adoption of a combination of CSA innovations (as opposed to individual innovations) is greatly associated with augmented cereal productivity, legume productivity, farm and household income. The IPWRA estimates show that adopting CA only, DTM & IL and DTM, IL&CA significantly impacted on cereal productivity with ATET coefficients of 0.291, 0.268 and 0.378 respectively. Adoption of the full CSA package had far greater impact on cereal productivity.

For legume productivity, the results show a similar trend; CA adoption only had a positive ATET of 0.471, DTM adoption only with a positive ATET of 0.449, DTM & CA with ATET of 0.504, DTM & IL with an ATET coefficient of 0.669 and the full package (DTM, CA& IL) with an ATET coefficient of 0.753 which is far greater than that of other packages.

Table 4
Impact of multiple adoption of climate-smart agriculture technologies on productivity and income in Malawi and Zimbabwe.

VARIABLES	Cereal productivity	Legume productivity	Farm income	Household income
CA vs No adoption	0.291**	0.471*	1.095**	0.542**
	(0.148)	(0.241)	(0.427)	(0.212)
IL vs No adoption	−0.256	0.0566	1.248*	0.824***
	(0.543)	(0.318)	(0.680)	(0.308)
IL & CA vs No adoption	0.304	0.376	1.682***	0.661***
	(0.213)	(0.307)	(0.442)	(0.239)
DTM vs No adoption	0.103	0.449**	0.766**	0.146
	(0.151)	(0.219)	(0.320)	(0.198)
DTM & CA vs No adoption	0.0918	0.504**	1.244***	0.565***
	(0.194)	(0.256)	(0.355)	(0.215)
DTM & IL vs No adoption	0.268*	0.669**	1.628***	0.689***
	(0.159)	(0.266)	(0.471)	(0.259)
DTM,IL & CA	0.378**	0.753***	1.095**	0.912***
	(0.162)	(0.224)	(0.427)	(0.199)
POMean	7.165***	6.071***	3.712***	5.360***
	(0.119)	(0.185)	(0.325)	(0.163)
Observations	1172	1172	1172	1172

Notes: Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; CA = Conservation agriculture; IL = improved legume; DTM = Drought tolerant maize; outcome variables are all in logarithm form.

The results also show that adopting all the CSA packages significantly influenced farm income. Adoption of CA only, IL only, DTM only significantly influenced farm income with ATET coefficients of 1.095, 1.248, and 0.766 respectively. The CSA packages of IL&CA, DTM &CA, and DTM, IL&CA had positive significant with ATET coefficients of 1.682, 1.244, and 1.095 respectively. For farm income IL &CA, and DTM & IL seemed to have greater impact on farm income.

Considering, total household income as the outcome variable, results show that adopting the full CSA package (DTM, CA & IL) had far greater impact as compared to other packages. ATET coefficients for CA only, IL only, IL&CA, DTM&CA, DTM&IL, and DTM, IL, &CA testify the result as they were found to be 0.542, 0.824, 0.661, 0.565, 0.689, and 0.912 respectively.

Largely, the results show significant differential impacts of adopting CSA innovations (CA, DTM&IL) in isolation and in combinations at farm household level. Adopting innovations in combinations seem to benefit the farmers more than as individual packages. The complementarities of the innovations in improving farmer resilience to climate change effects and overcoming other productivity related challenges at the farm level could explain the enhanced impacts of adopting packages in combination. The next sub-section analyses the impact by studied country and gender of farmer.

3.4. Heterogeneities in impact of climate-smart agriculture innovations on productivity and income

3.4.1. Adoption impacts by country

Adoption impacts by country show that in Malawi, adoption of IL only, DTM only, DTM&IL, and all the packages (DTM, CA & IL) significantly influenced cereal productivity whilst adoption of DTM only, and all the packages (DTM, CA & IL) significantly impacted on cereal yield in Zimbabwe. In Malawi, adoption of DTM&IL in combination had the greatest impact on cereal yield whilst in Zimbabwe, adoption of all the CSA packages had the greatest impact on cereal productivity (see Table 5).

Further, only adoption of DTM & CA significantly impacted on legume productivity in Malawi, whilst in Zimbabwe, CA only, DTM only, IL&CA, DTM&IL and all (DTM, CA &IL) significantly impacted on legume productivity. In addition, in Malawi, adoption of IL only and all the packages (DT, CA, &IL) significantly impacted on farm income, whilst in Zimbabwe, the individual and combination of CSA innovations positively and significantly impacted on farm income. Also, in Malawi adoption of IL only, DTM&CA, DTM&IL and all the packages in combination (IL, CA, &DTM) significantly impacted on total household income, whilst in Zimbabwe, CA only, IL only, DTM&IL, and DTM, CA& IL combination, all significantly impacted on total household income (Table 5).

Results continue to endorse the importance of CSA innovations on productivity and income and the enhanced impact of different combination of the innovations on productivity and income in both countries.

3.4.2. Adoption impacts by gender of farmer

Assessing the impact of differentiated CSA innovations adoption impacts by gender of farmer results portray that CSA innovations particularly in combinations enhance productivity and income irrespective of gender of farmer. In the male sub-sample, adoption of CA only and IL only, DTM&IL and DTM, CA&IL had a positive and significant impact on cereal productivity, whilst in the female sub-sample CA only, IL&CA, and all the CSA innovations (CA, DTM & IL) had a positive and significant impact on cereal productivity (see Table 6).

Also, adoption of CA only, DTM only, DTM & IL, and all the innovations (DTM, CA& IL) significantly impacted on legume

Table 5
Impact of multiple adoption of climate-smart agriculture technologies on productivity and income by country.

	Malawi				Zimbabwe			
	Cereal productivity	Legume productivity	Farm income	Household income	Cereal productivity	Legume productivity	Farm income	Household income
ATET								
CA vs No adoption	0.423	−0.234	−0.328	0.138	0.325	1.339***	2.278***	0.799**
	(0.322)	(0.244)	(0.464)	(0.229)	(0.265)	(0.374)	(0.606)	(0.367)
IL vs No adoption	0.603*	−0.214	1.407***	0.661**	−0.321	−0.439	3.131**	1.539***
	(0.341)	(0.318)	(0.454)	(0.307)	(0.822)	(1.028)	(1.222)	(0.566)
IL & CA vs No adoption	0.424	−0.244	−0.103	0.087	0.230	1.278**	2.668***	0.569
	(0.313)	(0.389)	(0.408)	(0.242)	(0.283)	(0.526)	(0.575)	(0.452)
DTM vs No adoption	0.527*	−0.238	0.087	0.245	0.216**	1.161***	0.707	−0.362
	(0.309)	(0.361)	(0.376)	(0.226)	(0.246)	(0.366)	(0.484)	(0.373)
DTM & CA vs No adoption	0.499	0.397*	0.421	0.483**	−0.091	0.687	1.347**	0.232
	(0.335)	(0.228)	(0.380)	(0.235)	(0.259)	(0.635)	(0.568)	(0.375)
DTM & IL vs No adoption	0.746**	0.160	0.424	0.388*	−0.038	1.376***	2.631***	0.910*
	(0.310)	(0.185)	(0.398)	(0.222)	(0.276)	(0.490)	(0.718)	(0.498)
DTM,IL & CA	0.589*	0.187	0.791**	0.716***	0.445*	1.421***	2.698***	0.892**
CA vs No adoption	(0.324)	(0.172)	(0.363)	(0.222)	(0.280)	(0.388)	(0.516)	(0.355)
POmean	7.106***	6.565***	5.063***	5.752***	7.045***	5.451***	2.615***	5.118***
	(0.292)	(0.099)	(0.313)	(0.196)	(0.238)	(0.333)	(0.415)	(0.268)
N	572	572	572	572	600	600	600	600

Standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 6
Impact of multiple adoption of climate-smart agriculture technologies on productivity and income by gender in Malawi and Zimbabwe.

	Male				Female			
	Cereal productivity	Legume productivity	Farm income	Household income	Cereal productivity	Legume productivity	Farm income	Household income
Treatments								
CA vs No adoption	0.285*	0.629**	1.050**	0.535**	0.625*	0.440	0.825*	0.460
	(0.170)	(0.277)	(0.438)	(0.246)	(0.362)	(0.446)	(0.466)	(0.416)
IL vs No adoption	0.420**	0.015	1.882***	1.083***	−0.942	0.271	−0.590	0.443
	(0.207)	(0.516)	(0.491)	(0.321)	(1.525)	(0.477)	(1.556)	(0.488)
IL & CA vs No adoption	0.193	0.491	1.346***	0.548**	0.929**	1.212	2.427***	1.542***
	(0.266)	(0.308)	(0.413)	(0.261)	(0.440)	(0.961)	(0.578)	(0.500)
DTM vs No adoption	0.036	0.694***	0.551*	−0.031	0.165	0.243	−0.137	−0.136
	(0.158)	(0.238)	(0.333)	(0.230)	(0.386)	(0.505)	(0.544)	(0.588)
DTM & CA vs No adoption	0.097	0.356	0.845**	0.314	−0.319	0.233	0.786	0.448
	(0.189)	(0.397)	(0.403)	(0.248)	(0.837)	(1.165)	(0.646)	(0.733)
DTM & IL vs No adoption	0.412**	0.870***	1.613***	0.709***	0.287	0.398	0.254	−0.080
	(0.181)	(0.281)	(0.393)	(0.237)	(0.489)	(0.777)	(0.848)	(0.716)
DTM,IL & CA	0.397**	0.827***	1.844***	0.777***	0.898**	1.051**	1.807***	0.993*
	(0.180)	(0.295)	(0.339)	(0.231)	(0.397)	(0.457)	(0.596)	(0.581)
POmean	7.170***	5.958***	3.806***	5.463***	6.837***	5.908***	3.774***	5.027***
	(0.134)	(0.227)	(0.295)	(0.179)	(0.348)	(0.362)	(0.362)	(0.247)
N	923	923	923	923	249	249	249	249

Standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

productivity in the male sub-sample, whilst adopting all the innovations (DTM, CA&IL) in combination significantly impacted on legume productivity in the female sub-sample.

Further, all CSA treatment categories significantly impacted on farm income in the male sub-sample whilst adopting only CA only, IL&CA and all (CSA, DTM&IL) significantly impacted on farm income in the female-sub-sample. Also, adopting IL&CA in combination, and adopting all the three innovations (DTM, CA, IL) simultaneously significantly impacted on total household income in the female sub-sample whilst in the male sub-sample, adopting CA only, IL&CA, DTM &IL and adopting all the innovations (IL, CA&DTM) at once significantly impacted on total household income. Still, results show the differential impacts of adopting CSA innovations individually and in combination and enhanced impact of adopting them in combination irrespective of gender of farmer (Table 6).

3.4.3. Overall discussion: impact of CSA innovations

Overall, results point to the importance of CSA innovations at farmer level in building resilience to climate change and other productivity related challenges on the farm. Adoption of CSA innovations reduces the impacts of climate change on crop productivity and farmer incomes. The benefits of CSA innovations are greater when complementary CSA innovations like improved legume, drought tolerant maize and conservation agriculture are adopted in various combinations. The enhanced impact of adopting the innovations possibly arise, due to the combined effect on improving soil nutrient use, soil moisture retention, fertility and adaptation of legume and cereal crops to moisture, pests and diseases stress. Results conform to emerging literature that has shown adoption of agricultural technologies in combination to have an enhanced impact on productivity, income and other welfare related variables (Khonje et al., 2018; Makate et al., 2017a; Tambo and Mockshell, 2018; Teklewold et al., 2013b; Wainaina et al.,

2017). For instance, Khonje et al. (2018) found joint adoption of multiple agriculture technologies to have greater impacts on crop yields, household income and poverty than adopting individual components. Also (Teklewold et al. (2013b); Wainaina et al. (2017)), and Makate et al. (2017a) found sustainable agricultural practices to yield greater impacts on productivity and income in smallholder farming. More so, adopting conservation agriculture packages in combination were found to yield greater impacts on income in a study by Tambo and Mockshell (2018). Almost similar trends were observed by farmer country of residence and by gender which further confirm the importance of adopting CSA innovations in combination for greater productivity and income.

4. Conclusions and recommendations

The research and development community concerned with welfare of smallholder farmers in developing countries has found increased promotion of CSA innovations vital in a bid to improve climate resilience. Adopting improved legume and cereal crop varieties resistant to drought, pest and diseases and conservation farming are some of the approaches highly promoted in smallholder farming in southern Africa. Improved legume varieties are highly important for soil nutrition management, stress (moisture, heat, disease & pest) management, while drought tolerant maize varieties are highly important for water stress management (drought) among other benefits. Conservation agriculture is also highly important for improved soil fertility, soil temperature regulation, soil moisture management among other benefits. In combination, conservation farming, and adoption of improved legume and drought tolerant maize varieties can have enhanced impacts on farm yields, income and farmer welfare. However, adopting more than one of the innovations for the smallholder farmer can demand extra resources for the smallholder farmer which is often a huge constrain for the low-resourced smallholder farmers in southern Africa. This study therefore evaluates the adoption and impact dynamics of adoption of conservation agriculture, drought tolerant maize varieties and improved legumes individually and in combination in two southern African countries Malawi and Zimbabwe. Determinants of individual and combined implementation of the three innovations and their differential impacts on crop productivity and income are studied.

The study outcomes have shown multiple adoption of improved legume, conservation agriculture and drought tolerant maize in combination to be essentially explained by access to resources (fertilizer, income, credit and information (through extension)). Education and land size holding. Greater access to resources enhances multiple adoptions of the climate-smart innovations. Also, the CSA innovations impact positively on crop productivity and income both individually and in combination. However, impacts are evidently greater for adopting innovations in combination than individually. Results were however, not 100% uniform across different geographical and gender contexts which highlight the importance of adhering to local specific contexts and addressing female farmer constraints when promoting adoption of multiple CSA innovations in smallholder farming. In conclusion, farmers are better off if they adopt beneficial synergistic CSA innovations such as drought tolerant maize, improved legume varieties and conservation agriculture in combination as they offer superior benefits towards adapting agriculture to climate variability and change. Also, better resourced farmers have a distinct advantage in adopting such multiple CSA innovations.

Results suggest for enhanced institutional and policy efforts towards reducing constraints of adopting multiple CSA innovations in smallholder farming. Access to financial resources, education, adequate land, and effective extension services can potentially assist farmers in building resilience to climate variability and change through multiple adoptions of conservation agriculture, improved legume and drought tolerant maize. In other words, for building adequate resilience of smallholder farmers to climate variability and change through multiple adoption of beneficial CSA innovations, governments and private sector should work tirelessly to improve farmer education and access to key resources (land, finance, extension, labour etc.). Improving the resource base for farmers will significantly enhance their propensity to adopt multiple CSA innovations. However, promotion of innovations and dealing with constraints of adoption must be local context specific, and gender sensitive for maximum impact.

The study is not without limitations. Relying on cross-sectional household level data did not allow the analysis to capture adoption and impact dynamics of CSA innovations through time. Also, relying on improved legume, CA and drought tolerant maize as only CSA innovations limited climate adaptation options embraced by other farmers. Adaptation is very much local context-specific and in practice, farmers can adopt more than three CSA innovations. Despite the noted limitations, the study makes significant contributions to literature on climate change adaptation in smallholder agriculture as CA, drought tolerant maize and improved legumes are highly important innovations promoted for farmers in southern Africa to cope with climate change and variability effects.

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Availability of supporting data

Data for this study can be obtained from CIAT Dataverse.
Repository URL: https://dataverse.harvard.edu/dataverse/CIAT.

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